ASIAN JOURNAL OF FORESTRY
Volume 8, Number 2, December 2024 E-ISSN: 2580-2844
Pages: 147-157 DOI: 10.13057/asianjfor/r080205

Identifying the factors that influence the decision of farmers in the Imam Sahib District of Kunduz Province, Afghanistan to plant trees

NAJIBULLAH OMERKHIL[1,♥], LARAIB AHMAD[2], SAFIULLAH KHURRAM[3]
[1]Forestry and Natural Resources Department, Faculty of Agriculture, Kunduz University. Kunduz City, Second District, 3501, Afghanistan. Tel.: +93-0-785356463, ♥email: n.omerkhilagr@gmail.com
[2]Forest Research Institute (FRI). Chakarata Road, New Forest, P.O, Dehradun, 248001, India
[3]Forestry and Natural Resources Department, Faculty of Agriculture, Kabul University. Jamal Mina, D-1006, Kabul, Afghanistan

Manuscript received: 27 July 2024. Revision accepted: 10 November 2024.

Abstract. *Omerkhil N, Ahmad L, Khurram S. 2024. Identifying the factors that influence the decision of farmers in the Imam Sahib District of Kunduz Province, Afghanistan to plant trees. Asian J For 8: 147-157.* For years, agroforestry has been employed as a sustainable management approach to enhance and provide services and products traditionally obtained from natural forests. This study focuses to analyze the factors that influence farmers' farm tree planting decisions. We focused on the Imam Sahib District of Kunduz Province, Afghanistan and collected data from 160 households in 32 villages, and within each village, five farmer families randomly selected for a face-to-face interview and data collection using a randomized snowball sampling strategy. A binary logistic regression model was developed using the acquired data to identify the features influencing farmers' tree-planting decisions. The findings reveal that several variables affect the propensity of tree planting and the intensity of agroforestry technology. These factors include the income of the head of farmer households, availability of irrigated farmland, large cropping land, and prior tree planting experience. Conversely, factors such as education, limited access to planting materials, large family size, availability of tree seedlings, and age of the head of the households, loan, and insurance facilities can influence farmers' decisions and adaptation practices. So far, education plays an important role in strengthening farmers' understanding of the limits, opportunities, and needs of new technologies in the form of short-term training. This might mitigate the unfavorable relationship between the age of the family head and willingness to use agroforestry practices on their farmland. These findings, particularly the potential of education to improve farmers' adoption of agroforestry practices, can help strengthen the National Agroforestry Policy to promote tree planting among the farmers, achieve targets for tree coverage, and reduce pressure on natural forests in Kunduz and other provinces and countries with similar situations.

Keywords: Agroforestry, binary logistic regression, farmland, household

INTRODUCTION

The escalating demand for forest products, such as wood fuel, poles, furniture, and materials for housing and development, has driven significant deforestation in developing nations.This trend reflects a concerning reliance on these resources (Kulindwa 2016; Brockhaus et al. 2021). Large and small-scale agriculture and the harvesting of trees for fuel wood and timber are the main culprits in the worldwide loss of natural forest cover (Adesina et al. 2000; Brockhaus et al. 2021). Conversely, agroforestry is an age-old practice integrating trees with crop and livestock production systems (Kulindwa 2016; Brockhaus et al. 2021). Agroforestry now seen as a crucial approach to providing forest functions and products previously obtained from natural forests (Kulindwa 2016). The system aims to diversify and sustain production for enhanced benefits to land users, comprising social-economical, ecological, and environmental benefits (Ashraf et al. 2018). Even though various circumstances, such as the worsening economic situation in many developing countries, have led to the rising interest in combining trees with crops and animals' production system, there are still significant challenges to doing so successfully (Akinnifesi et al. 2008). Growing interest in farming systems, population pressure leading to scarcity and degradation of land, increased tropical deforestation, and intercropping and environmental issues since the 1970s, the benefits of this management system are becoming more apparent (Akinnifesi et al. 2008; Basamba et al. 2016; Kulindwa 2016; Magugu et al. 2018).

Tree planting is becoming an increasingly appealing choice, especially for smallholder farmers involved in low-investment agriculture and low-technology agricultural systems that generally combine a mix of subsistence and market output (Kulindwa 2016; Ashraf et al. 2018). Agroforestry has expanded rapidly on small farms facing forest scarcity, as these systems reduce the cost of tree production through integrated crop and livestock farming (Ficko and Boncina 2013). Agroforestry, is the deliberate integration of planting trees and shrubs with cultivated plants along with livestock production (training) systems in agricultural areas. This is a novel technique that utilized to offer economic, social, and environmental potential (Tremblay et al. 2014; NEPA 2019), evolving as part of intensive ecologically-based farmland management focused on sustainable resource consumption and providing cost-effective alternatives within given economic, social, and environmental settings (Basamba et al. 2016; Magugu et al. 2018). Increasing agricultural productivity and diversity and generating items like fuelwood, construction materials, food, medicine, and fodder, tree plantation on the farmlands has the capacity and potential to decrease food shortage and poverty and may be put to effective use in food safety and poverty decline globally (Neupane et al. 2002; Magugu et al. 2018). Planted trees in agriculture farms are anticipated to supply forest products that were previously obtained from natural forest ecosystems (Lambert and Ozioma 2011). Agroforestry provides opportunities to achieve various goals, such as creating a suitable small-scale climate for high-value plants and appropriate ecological processes, especially for sustainable agricultural land use (Magugu et al. 2018). The deliberate integration of crops in to the trees and shrubs with the animal production system is a suitable framework for water and soil protection and conservation at a reasonable price compared to traditional methods of trace (Neupane et al. 2002), and the functions of forest ecosystems are significantly improved by planting industrial fast-growth trees (Basamba et al. 2016).

High population pressure and an increased demand for food have caused in the degradation and deforestation of huge natural forest cover areas in Afghanistan, resulting in a loss in natural forest products (Groninger and John 2014; FAO 2018). Recent assessments indicate that out of the total land area of Afghanistan (652,860 km^2), only 2.1% is covered by natural forests, and the remaining natural forests have poor tree cover (Reddy and Saranya 2017; Shalizi et al. 2018; FAO 2018; NEPA 2019; Omerkhil et al. 2020). The last four decades of conflict in Afghanistan have caused a decline in forestland cover, likely to continue due to over-exploitation, deforestation, climate change, and developing activities (FAO 2018; Omerkhil et al. 2020; Khurram et al. 2024). To protect natural forest concerns, the lack of industrial and fuel wood, timber and non-timber forest products, has necessitated the implementation of serious measures to protect and preserve the remaining forests. These measures have led to limited timber and wood extraction, reducing forest production (Reddy and Saranya 2017). The fuel and industrial wood production in agriculture farmlands through the planting of fast-growing trees such as *Amygdalus communis*, *Fraxinus xanthoxyloides*, *Eucalyptus globulus*, *Elaeagnus angustifolia*, *Morus alba*, *Platanus orientalis*, *Populus alba*, *Robinia pseudoacacia*, *Prunus armeniaca* and *Salix aemophyla*, both in the form of woodlot and agroforestry system has the potential as a partial solution to the increasing wood shortage (FAO 2003; Groninger and John 2014; Omerkhil et al. 2020).

The Afghanistan forestry policy recognizes agroforestry for the provision of poles, timber, firewood, and even non-wood products like fruits (NEPA 2019) to aid communities, farmers, entrepreneurs, and institutions in agroforestry development. The policy also includes provisions for strengthening the capacity of government agencies, private suppliers, Community-Based Organizations (CBOs), and Non-Governmental Organizations (NGOs), to offer advisory and extension services (NEPA 2019; Omerkhil et al. 2020). There has been no study to identify the factors influencing the enhancfement of the adoption of agroforestry technologies in Afghanistan, particularly in northeastern region. Even though the Ministry of Agriculture, Irrigation and Livestock (MAIL), and National Environmental Protection Agency (NEPA) of Afghanistan have been involved in the widespread extension of these on-farm technologies, particularly in North Eastern Afghanistan, as well as the Imam Sahib district (FAO 2003; MAIL 2019; NEPA 2019). Considering that "adaptation of new technology" is a local event that can differ with time and geographical location (Ali and Erenstein 2017), it is always possible that a need to develop a realistic perception of adaptation practices by farmers worldwide is necessary to negotiate the acceptance of new technology in agriculture farm positively. There is a compelling need to design agroforestry research that determine unique, localized factors that influence farmers' farm tree planning decisions because of agroforestry importance and associated activities for the livelihoods of rural areas and the overall socio-economic development of Afghanistan. This can be achieved through estimating the farmers' decision while considering the area's demographic, socio-economic, and natural factors, as their combined interaction often determines a farmer's choice and adaptation for tree plantation. Therefore, this study aims to evaluate the influence of socio-demographic, economic, and natural factors on the decision of farmers to plant or not to plant trees on their farmlands in the conflict-stricken Imam Sahib District of Kunduz Province, Afghanistan. Previous studies generally address agroforestry in broader contexts or other regions; this study employs a binary logistic regression model to pinpoint precise local factors, such as income levels, land availability, irrigation, and past tree-planting experience that uniquely affect tree-planting decisions in a highly vulnerable and under-researched area. Additionally, this study provides targeted policy recommendations that align with Afghanistan's National Agroforestry Policy, which has not been widely discussed or evaluated in prior research.

MATERIALS AND METHODS

Study site description

This study focused on Imam Sahib District of Kunduz Province, Afghanistan. Kunduz has more than 1.1 million population distributed in a total geographical area of 7,666.7 kilometers square in six official and three temporary districts, of which 88% is foot-plains and 12% is semi-mountainous or mountainous terrain with an average elevation of 405 meters above sea level (Sadiq et al. 2019). Among them, 25.11% of the geographical area of this province, which is 193,983 hectares, is allocated to agricultural lands (FAO 2012). Owing to its unique natural topography and a pattern of different geographical landscape, that presents exceptional socio-demographic and economic dynamics as the context of this study. The Imam Sahib District is further extended into the 189 major and minor villages (CSO 2017). Around its total land area of 25.11% is cultivable and grown 35 different crops (USAID 2017), whereas 74% of the cultivated farmland area is concentrated in four southeastern and northern districts in the foot plain near the center of Kunduz and Amu River basin (FAO 2012; CSO 2017). The rest geographical area of these districts is not suitable for agricultural crop cultivation but is only used for livestock rearing due to the raised slope and mountainous terrain (Sadiq et al. 2019). Producing both rain-fed and irrigated vegetables, cereal, oil seed, cotton, and fruit crops, Kunduz serves as the region's food basket (Sadiq et al. 2019; MAIL 2019). Due to the short growing season in mountainous terrain, only one agrarian crop is cultivated annually at higher elevations, while in plain areas, two crops can grow (Aich and Khoshbeen 2016). Agroforestry and livestock are other important sources of revenue for farmer households in this district. An average the monthly income of households in the study region is around 23,353 Afghani (333. 61 $), (MAIL 2019).

Imam Sahib District is one of the largest districts in Kunduz Province located in the coordinates of N 37° 12′ 68″ and E 68° 46′ 21″ in the northeast of the country, with a mean altitude of 365 meters above sea level. Dasht-i-Archi and Qalizal Districts of Kunduz Province surround Imam Sahib to the southeast and west, Tajikistan to the north, and Kunduz center to the south (Figure 1). The total geographical space of Imam Sahib District is 1,610 km^2 which is spread to 189 major and minor villages across the region (FAO 2012; CSO 2017). Imam Sahib is also distinctive in undulating topography with plain, river valleys, hills, and mountains. The total population of this district in 2019 was state to be 288,603 individuals, with men 163,824 and females 124,779, spread in uneven proportions as the province's second-largest and most populous district. Livestock rearing and agriculture are the main sources of income for dwellers, and around 70% of its people are engaged in farm activities and livestock raising (CSO 2017; MAIL 2019). According to Copen climate classification, its climate is a local steppe and rain deficient (Belda et al. 2014), with a mean annual temperature of 17.1°C. The coldest months are January and February, at 3.4°C, and July and August, the hottest months of the year, with an average temperature of 30.2°C (Belda et al. 2014; WMO 2018).

Imam Sahib District has 2,600 km^2 of Tigai and riparian forest near the bank of Amu River and foothill. This forest is home to various tree species, including reeds (*Phragmites australis*) grass, *Tamarix* spp., willows (*Salix* spp.), and a strip of *Pistaci* and *Elaegnus* spp. (Groninger and John 2014; Moheb et al. 2016; FAO 2016). Based on the ecological importance and scarcity of this forest ecosystem in Afghanistan, the central government has declared the Imam Sahib riparian forest a protected forest to preserve its functioning and ecological values for future generations (UNEP 2013; Aich and Khoshbeen 2016).

Sampling and data collection

The targeted population of present study was all Imam Sahib District farmers who leave a conflict-stricken rural area of Afghanistan and predominantly practiced agroforestry and dispersed across 189 minor and major villages. Out of 189 villages of the district, 32 villages, and within each village, five farmer families randomly selected for a face-to-face interview and data collection using a randomized snowball sampling strategy. A pre-tested questionnaire, including a consent criterion at the beginning, ensuring that respondents were fully aware and participated voluntarily, produced an aggregate of 160 farmer families from 32 villages. In-person interviews with key informants were among the other forms of data collecting used in the research, focus group discussion, field visits, and observation to acquire information about farmers' on-farm tree planting aims, and subsequently, the variables inducing their on- farm tree-growing decisions.

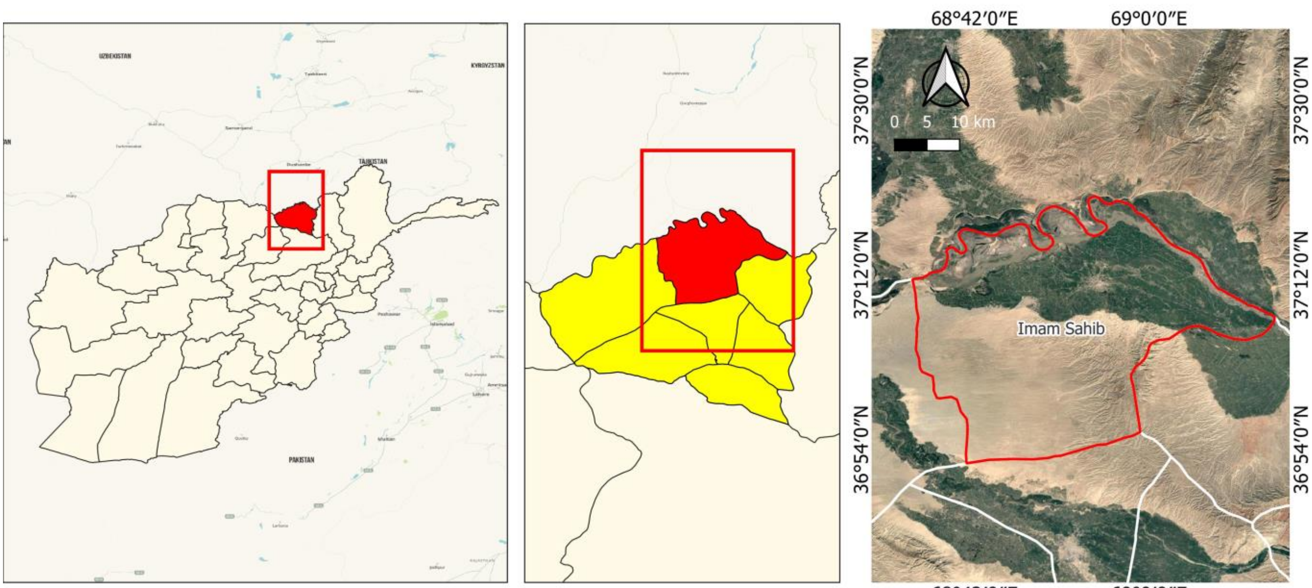

Figure 1. Study site map in Imam Sahib District, Kunduz, Afghanistan

Table 1. Explanation of variables considered in statistical analysis of binary logistic regression model for the present study

Parameter name	Acronym	Coding	Descriptions	References
Age	V1	≥ 45 years old = 1, else = 0 (dummy)	Age of family head in years	Ashraf et al. (2018)
Education	V2	1 up to high school, else = 0 (dummy)	Household head formal education level in years	Suyanto et al. (2005)
Family size	V3	1 = ≥ 8 member, else = 0 (dummy)	Number of members in the family	Ficko and Boncina (2013)
Seed facility	V4	1= Yes, 0 = No (dummy)	Seed adequacy and availability to the farmers	Brockhaus et al. (2021)
Irrigated land	V5	1= Yes, 0 = No (dummy)	Irrigated farmland ownership of farmers	Dhiman (2012)
Monthly income	V6	1 if > 15000 AFGs, else = 0 (dummy)	Monthly income of farmers	Jara-Rojas et al. (2020)
Agriculture land	V7	In hectare (continues)	Total cultivated land of farmers	Gebru et al. (2019)
Tree planting experiences	V8	In years (continues)	On-farm tree planting experience of farmers	Ashraf et al. (2018)
Scientific technique applied	V9	1= Yes, 0 = No (dummy)	The scientific technique used for tree plantations by farmers	Jara-Rojas et al. (2020)
Loan availability	V10	1= Yes, 0 = No (dummy)	Awareness about loan facilities and availability	Thangata and Alavalapati (2003)
Insurance awareness	V11	Yes = 1, No = 0 (dummy)	Household awareness related to crop insurance facilities	Place et al. (2012)
Institutional support	V12	1= Yes, 0 = No (dummy)	Institutional support for tree plantations of farmers	Gebru et al. (2019)
Tree harvesting right	V13	1= Yes, 0 = No (dummy)	Farmers rights for trees harvesting and its transportation to the market	Ashraf et al. (2018)
Awareness of the tree plantation program	V14	1= Yes, 0 = No (dummy)	Farmers' awareness about tree plantation programs	Saha et al. (2018)

For primary data collection, a semi-structured pre-tested questionnaire (open and closed-ended) and key squalor interviews were used to confirm the adequacy and precision of the data and information acquired while preventing uncertainty in the questionnaire and key informant interviews, previously from field visits and observations a pilot survey was done to verify the interviewers' feedbacks. The questions comprised the farmer's household socio-demographic and economic status, crops and tree cultivation practices, current land use, institutional and other supporting factors, resource endowment, and main problems for farm activities; the details of these variables characterized in Table 1. Face-to-face interviews, focus group discussions, and field surveys conducted during March and April 2022 by the researchers' in native languages (Pashto and Dari) to confirm that the interviewer understood the designed questions. Where possible, we spoke with the heads of farmer households directly; if that was not possible, we spoke with the next-most senior member of farmer households. On average, each interview completed in 30 minutes, and the researchers used a questionnaire sheet to note the respondents' answers. Supplementary informant group discussions with farmers and field visits helped raise this study to comprehensively understand numerous socio-demographic, economic, and natural factors and constraints on the farm's tree plantations.

Model specification and data analysis

Adopting and implementing new activities is a long process that includes information processing and deciding to enhance farmers' utilization of their own productive resources (Saha et al. 2018). Ultimately, the decision making of whether or not to adopt new technology on their farmlands will be made after the heads of farmer households go through a series of phases of introspection and experimentation designed to increase their knowledge and technical understanding of the benefits and drawbacks of doing so (Saha et al. 2018; Shin et al. 2020). The age and education level of the family head and family sizes, the amount of land available, the number of available workers, the gender distribution within the household, the availability of transportation, the proximity to the market, the availability of planting materials, and the availability of supporting services like loan and insurance facilities, institutional support, and extension services can all have an impact on a farmer household's final decision (Ashraf et al. 2018; Saha et al. 2018). External determinants include things like product pricing and even government laws, in contrast, internal ones include the scat-redness of land pieces, land quality, proximity to irrigation facilities, and other natural and environmental conditions (Thangata and Alavalapati 2003; Suyanto et al. 2005; Place et al. 2012).

Considering these factors, it was determined that the farmers' decision-making and adoption of on-farm tree planting by the farmer households can be characterized using the binary logistic regression statistical model. This statistical model aims to measure the predicted influence of a set of descriptive characteristics on a dichotomous outcome (in this case, the likelihood of a farmer deciding to plant trees on their acreage) based on the values of independent variables. This study's dependent variable is whether farmers have adopted tree-planting practices, and it is given a value of one (1) if, farmers have adopted tree planting and a value of zero (0) otherwise. Statistical trials were done by the maximum likelihood technique using SPSS 22, to estimate the assigned parameters of the model. Some contextual variables for the present study were regressed with the dependent variable *Y* to quantify the influencing factors (β_i).

The equation (population model) to be estimate based on the following explanatory variables is as follows:

E(*Y*) = β_0 + β_1*V1 + β_2*V2 + β_3*V3 + β_4* V4 ++ β_8*V5 + β_6*V6 + β_5* V7 + + β_7*V8 + β_9* V12 + β_{10}*V10 + β_{11}*V11 + β_{12}*V13 + β_{13}*V14 + ε

Where, β_is are population parameters and ε is an error term of the model to be estimated.

The selection of variables shown in Table 1 is based on the author's knowledge and different promises of agricultural decision-making. It illustrates the explanatory variables in detail involved in the population model. This model hypothesizes that the explanatory factors reflect the tree planting adaptation choice (Thangata and Alavalapati 2003; Suyanto et al. 2005; Place et al. 2012). The continuous explanatory variables, except the dichotomous V7 and V8 variables converted to dummy variables. The dummy variables categorized based on the available sample data and the Interviewers' replies specific to the variables. The elder head of the farmer's household has greater skills in managing a family, so V1 is reflected as a dummy variable due to their high family administration experience (beyond 45 years was judged to achieve the experiences). As a result, they will implement any new technology in farms with risk management capability and aversion (Buyinza and Wambede 2008; Place et al. 2012; Ashraf et al. 2018). Since individuals with a grade 12 (high school) education level are more able to study, enjoy, and comprehend tree planting, the education level was transformed into a dummy variable as suggested by (Neupane et al. 2002; Sidibe 2005). Due to the high illiteracy rate among Afghan farmers, they cultivate and grow trees on their farmlands based on their experiences in tree plantation and contacts with their neighbor farmers. It was expected that a farmer with a (high school) education level, who knows very little about tree plantation and agriculture would have a similar capacity to enjoy, study, and comprehend tree planting. A family with eight or more individuals considered a big family and a dummy variable.

The independent variables V1 (household head age) and V3 (family size) describe the agricultural labor source. The education level of the farmer's household heads (V2) is a personal feature that aids decision-making (Sidibe 2005; Saha et al. 2018). V4 denotes insufficient nearby seed sources, V7 denotes the entire cultivated land area, and V5 denotes farmland with irrigation facilities. Both variables define on-farm tree plantation choice of farmers, whether to grow annual crops. The total monthly income of the farmer's household (V6) is associated with farmers' potential to invest in agricultural and farm activities, consisting of tree plantations (Place et al. 2012; Ashraf et al. 2018). V8 is (on-farm tree planting experiences in a year), and V9 describes applying the scientific technique for tree plantation and crops. V11 and V10 illustrate farmers' awareness of the insurance and loan facilities and availability (Zomer et al. 2007; Ashraf et al. 2018). At the same time, V12 and V13 represent farmers' institutional support and tree harvesting right, whereas V14 represents awareness of the tree plantation program (Buyinza and Wambede 2008; Ashraf et al. 2018). The odds ratios Exp (b) (exponents of variable) for each parameter were investigated to determine the influence of dependent variables on explanatory factors, and the Nagelkerke-R^2 statistic was used to estimate the model adequacy. The strength of the relationship was measured using Percent Concordant, Tau-a, and c-statistics, and Somer's-D statistic. The binary logistic regression statistic model was used to examine the Lemeshow and Hosmer goodness of fit (GOF) test. The acquired primary data was coded and analyzed using statistical software for social sciences (SPSS. 22).

RESULTS AND DISCUSSION

Socio-demographic status of sample farmers

Across Imam Sahib District, the living status of farmers was poor, with farmers living in small houses constructed from local materials, as observed during the survey. Most households depended on firewood for cooking and small solar panels for light. The distribution of respondents according to their age classes is shown in Table 2. The majority of Imam Sahib people (36.04%) were within 31-40 years, followed by age class of 16-30 years (31.31%), up to 15 years old (16.37%), 41-50 years (14.56%), while the age class above 65 years representing (1.37%) of the total population. Males consist (59.08%) of its population and females (40.91%). This implies that the population of this district was relatively young compared to the national level and actively involved in farming activities. According to Kinyili et al. (2020), as the age of the family head increases, so does the adoption of tree planting since younger farmers are more ready to take risks and have a long-term planning horizon than the elder family heads of farmers. The percentage of males is somewhat greater than that of females; this benefits agroforestry technology development.

Family size and dependency ratio

Imam Sahib District farmers followed a joint family culture, so the farmland could not be divided among the offspring. The large family concept has been prevalent for the generations due to the resource intactness and stringent livelihood options requiring a high labor force, and this indicates that farmer's households with a higher number of family members were further willing to adopt new on-farm activities like on-farm tree planting technologies related to those families with fewer family members. However, nowadays, the nuclear family concept is also in practice (19.37%,) respectively having a family size of up to four members (Table 2). The proportion of families mainly consisting of more than 12 members was very high (46.86%). There was a discrepancy between the results of this study and those of Ficko and Boncina (2013), and Shin et al. (2020), who found that farmers' larger family sizes were associated with greater adoption of on-farm tree planting. These results showed that a family with more members had a significant consequence, and they confirmed that there is a large number of working-age and active labor force in the population.

Household education level

Education is essential for human resource development, encompassing better health, nutrition, improved socio-economic opportunities, and a more pleasant and beneficial natural environment. The educational situation clearly shows society's awareness and likely future growth (Buyinza and Wambede 2008; Kinyili et al. 2020; Shin et al. 2020; and Brockhaus et al. 2021). The farmers' household-head education status analysis and their counterpart showed that illiteracy level was higher with a very small proportion of heads of household and their counterpart with education more than high school. The reason for the low education level among the head of the household was primarily not economic but rather geographical location and non-availability of school, as interviewers reported during the survey (Table 2). Respondents reported that the non-existence of road infrastructure and the very typical and hazardous footpaths on the hilly terrains were also factors responsible for low education. The children's educational status was also investigated during the survey. It was observed that although people of this district were aware of the merits of education, socio-economic and geographic constraints still forced most farmer families to withdraw their kids from school and get involved in farm and domestic activities. During the survey and field observations, it was observed that there were some farmers' families whose kids were totally involved in domestic and farm activities. The non-attendance of school by children was chiefly due to the non-availabilities of the schools near the villages or the involvement of kids in some socio-economic activities; these domestic duties, in the case of male children, included mainly the livestock rearing and in the case of female children, household affairs, in addition, observed during the survey. The results of this study are quite in line with the studies conducted by Faham et al. (2008), Dhiman (2012), Ficko and Boncina (2013), and Gebru et al. (2019).

Land holding size of farmers

Landholding overall and irrigated land are the most significant factors for rural households, especially once agriculture is the main profession. The proportion of households possessing a land area of more than 1 hectare was high (52.5%) in the region (Table 2), followed by 1-4 hectare (38.75%) and 4-8 hectare (8.75%). Therefore, the size of a farmer's property seems to be a significant factor in the farmer's selection for tree planting. This study's evaluation is consistent with the findings of other investigations (Lönnstedt 2012; Gebru et al. 2019; Shin et al. 2020); they reported that if all other circumstances remain constant, on-farm tree planting would rise if a farmer has enough farmland to produce enough food to sustain his family members, unlike a farmer with a tiny landholding.

Availability of loan and insurance facility

Loan and insurance availabilities are the main components of agriculture. Table 2 shows the proportion of households having awareness and access to agriculture loans and crop insurance facilities. Almost all households in the region (73.75%) were unaware of loan and crop insurance facilities. Farmers with access to many funding sources and loans are more likely to involve tree-planting practices on their farm than those without such options. According to the findings of Raina et al. (2011), Saha et al. (2018), and Jara-Rojas et al. (2020), loan availability and credit facility is a major problem in future on-farm tree planting.

Table 2. Socio-demographic descriptions of farmer's households living in the study region

Parameter	Frequency	Percentage (%)
Age (in years)		
Up to 15 years old	218	16.37
16-30 years old	417	31.31
31- 40 years old	480	36.04
41-50 years old	194	14.56
Above 65 years old	23	1.73
Gender		
Male	787	59.08
Female	545	40.91
Family size		
1-4	31	19.37
4-8	54	33.75
8-12	75	46.86
Education level		
Illiterate	870	64.26
Primary	176	13.61
Intermediate	132	10.20
Graduate	100	7.73
B.Sc.	29	2.24
Above B.Sc.	25	1.93
Agriculture land area (in hectare)		
>1	84	52.5
1-4	62	38.75
4-8	14	8.75
Family head awareness about loan and insurance facilities		
Yes	42	26.25
No	118	73.75

Table 3. Concise statistics of surveyed households' characteristics (N=160)

Variable name	Adopters		Non- adopters	
	Mean	**Standard division**	**Mean**	**Standard division**
Age of family head (in years)	43.38	11.38	12.10	43.38
Education level of HH (in years)	8.15	6.04	5.12	6.00
Family size of HH	6.11	2.89	2.88	7.13
Secondary occupation of HH	4.6	3.18	2.76	3.61
Agricultural land (in ha)	0.15	6	1.97	2.10
Irrigated land (in ha)	16.45	19.66	5.99	3.89
Tree planting experience of HH (in years)	75%	N=160	N=160	47%
Off-farm income HH	24.92	38.36	18.39	12.92
Total number of trees planted	-	-	-	20%
Income from planted trees	2	0.97	1.02	3
Awareness of HH about loan and insurance facilities	3	1.01	0.80	2

Table 4. Evaluated standard errors, coefficients, and other descriptive statistics of the binary logistic regression model

Variable name	Standard error (p-value)	Coefficient (b)	Upper CI	Lower CI	Probability (Odds ratio)	Exp (β)
CONSTANT	4.30 (0.62)	-2.62	3.99	-8.52	8.00	0.11
V1	3.15 (0.37)	-2.81	2.70	-7.75	7.00	0.08
V2	4.48 (0.06)	-9.54	0.05	-19.59	0.18	0.00
V3	2.90 (0.03)	-3.74	1.99	-9.93	4.00	0.04
V7	0.18 (0.05)	0.40	0.69	0.03	7.50	1.53
V6	4.60 (0.02)	11.08	18.36	1.79	4.30	38,852.10
V5	2.33 (0.04)	5.05	8.75	0.62	146.5	0.89
V8	0.32 (0.03)	0.63	0.91	0.09	5.30	1.90
V4	1.96 (0.07)	-4.19	0.13	-7.61	5.00	0.05
V11	8.39 (0.81)	3.15	18.43	-12.47	7.20	18.63
V10	6.32 (0.74)	1.35	17.05	-11.79	9.00	4.76

Note: Concordant Percent = 99.0 Somers' Tau-a = 0.163, D = 0.98, c = 0.99, Lemeshow and Hosmer Goodness-of-Fit Test = 0.51 (p = 0.99), Nagelkerke-R^2 = 0.84

Factors determining farmer's decision to plant trees

Table 3 presents the summary statistics of a few key attributes of adopters and non-adopters farmer households of Imam Sahib District of Kunduz Province. The information concerning these essential features is not supplied entirely for non-project and project heads of households since the changes in certain variables within the project and non-project farmers' households were considerably varied. On average, the adopter and non-adopter farmer's families were fairly varied in terms of the economic and socio-demographic features of the family head, such as education level, age, secondary profession, family size, irrigated farmland, and income from other sources. For instance, the average family size in terms of family members was 2.88 for non-adopters and 6.11 for adopters. The variation was significant at the 0.05% probability level; the results of current study are quite in harmony with the evaluation of Tefera and Lerra (2016), Saha et al. (2018), Gebru et al. (2019), Jara-Rojas et al. (2020), and Kinyili et al. (2020), who led the research that found, overall family size had a substantial influence. Similarly, the secondary occupation of heads of household was an average of 4.6 for adopters and 2.76 for non-adopters. The variation was highly significant at 0.05% probability level. Apart from a relatively higher household head age similarity among the non-adopters and adopters, both farmers' families had non-parallel cultural structures (Table 3). The proportion of farmers' households that adopted on-farm tree plantation was 90%, and non-adopted households were less than 10% of 160 sampled farmers' households. The field observation also confirmed this statistic. However, on-farms tree planting intensity is varied extremely, with the majority of farmers' households' heads having low to moderate on-farm tree planting activities on their farms; these evaluations conform to the results of Lönnstedt (2012), Basamba et al. (2016), Ashraf et al. (2018), Kinyili et al. (2020), and Brockhaus et al. (2021). According to their findings, farmers less likely to plant trees on their property are more likely to have a negative outlook on the potential benefits of other cultivable crop yields, water availability, soil health, and biodiversity.

The descriptive statistics illustrate that more on-farm tree planting being carried out among the farmers with the highest education level, and education level boosts the adaptation of more on-farm tree plantations in the farmlands. The farmers' households, with higher monthly income and more irrigated and agricultural land ownership follow this on-farm technology. When comparing farmers with different family sizes, those who adopted the practice had more family members, who helped around the house and on the farm. This means large family size provides an abundant labor supply with many members. On the other hand, small families with few numbers of family members are not liable to espouse tree plantations on their farmland for the reason of labor deficiencies. The results reported by Adesina et al. (2000), Akinnifesi et al. (2008), Faham et al. (2008), Cosmas et al. (2012), and Dhiman (2012), confirm the evaluation of this study as they described, on-farm tree planting adoption decision of farmers household was significantly influenced by the farmers' family size and household head education level. Tree planting adopters had more experience in agroforestry and general farming than non-adopters did. The results further indicated that the income from planted trees for adopters (2) was higher than non-adopters (1.02) on average. This demonstrates that farmers who benefit economically from their on-farm trees plantation are more inclined and are agree to adopt agroforestry practices. As family monthly income is one of the essential components in deciding the households' choice of on-farm tree planting, our findings are in concord with the evaluations of Sharma et al. (2009), Tremblay et al. (2014), and Kinyili et al. (2020), that the farmers' monthly income needs to adopt trees. With a rise in per capita income, a family's chances of becoming middle class raise dramatically. Table 2 summary statistics also show that agroforestry adopters were more likely to be aware of loan and crop insurance facilities than non-adopters. It suggesting that easy access to credit and knowledge of loan availabilities and insurance facilities are major motivators for the introduction of innovative farming practices, such as tree planting systems on farmland area (Lambert and Ozioma 2011; Magugu et al. 2018).

Analytical modeling of the binary logistic regression equation

A binary logistic regression model was used with the help of maximum likelihood estimation of parameters to investigate and measure the association between the explanatory factors and dependent variables that influence farmers' choice to accept tree planting on their farmlands. The evaluated variables show the adaptation manners of the farmer households. These variables include the farmers' family size, household head formal education level, age of family head, monthly income of the family, agriculture land, irrigated farm size, crop cultivation and tree planting experiences, seed facilities, awareness about loan and insurance facilities, and institutional support. According to the results of the significant likelihood ratio test, the estimated models that include both constant and explanatory factors provide a better fit to the data for the farmers than the models that include just the constant variables. Lemeshow and Hosmer's goodness-of-fit test yielded a small p-value, and Nagalkere's R^2 was very near to 1, indicating that the model was adequate. On the other hand, the highest relationship between expected likelihoods and acquired answers, i.e., the ratio of concordances, proposes that the assessed adopted model had an excellent descriptive ability. The area under the receiver functional trait curve, which confirms the power of the model shown by c, is also close to 1, the same finding is reported by Akinnifesi et al. (2008), Basamba et al. (2016), and Ashraf et al. (2018). Even though many of the coefficients in the model are statistically insignificant when considered separately, the investigation reveals a correlation between the log of odds of reflected explanatory variables and, by extension, the odds and likelihood of accepting on-farm tree planting practices. All the critical factors show the predicted symptoms, and the accepted theory of how the environment affects farmers' acceptance rate holds. Validating the current knowledge of how farmers' circumstances influence their accepting behaviors, all the significant factors show the expected symptoms. Insignificant coefficients and signs for family size and age suggest that these factors have no significant role in determining whether or not trees are planted on a farm (Table 4).

The monthly income of the family (V6), the area of agricultural land owned by farmer households (V7), irrigated cropping land area (V5), and the farmers' household head on-farm tree-planting experience (V8) are the most significant factors that are influencing on-farm tree planting adoption decision at the 0.05 confidence level. The model shows that, after adjusting for other factors, the monthly income of farmer's families, agricultural land area ownership, on-farm tree planting experience, and irrigated farmland size all positively influence the adoption of new on-farm technology. In probability terms, each of these estimated variables are more than 50% important. The odds ratio indicates that farmers household head monthly income has the highest contribution role to the implementation of tree planting on agricultural land, followed by the area of irrigated land in general and specifically by the number of family members, agricultural land without irrigation facilities, and the tree planting experience of the head of the farming household. The studies conducted by Ashraf et al. (2018), Magugu et al. (2018), and Saha et al. (2018) have practical implications for agricultural researchers, policymakers, and professionals, empowering them to make informed decisions and apply the knowledge in their work. The number of factors, including production goods, consumption goods, family income, and technical skills and knowledge in tree planting experience, which govern a farmer's risk, are all intertwined with the monthly income the farmer's family receives, which decides the risk. This evaluation is also in harmony with the reports of Lambert and Ozioma (2011), Lambert and Ozioma (2011), Tremblay et al. (2014), Tefera and Lerra (2016), and Kulindwa (2016), who illustrated farmers' monthly income matters for their adoption of on-farm trees plantation, and a rise in income per person greatly raises the household's chances of doing so. These factors, in combination, simplify the farmers' on-farm tree planting decisions and adoption.

Given the current resource mix and environmental conditions, the projected outcomes highlight that irrigated farmland is associated with greater incomes, quality of life, and adopting innovative creativities, such as on-farm tree planting. That is to say, farmers with high-quality farmland may choose between planting trees on their property and growing a variety of cash crops that will provide them with the income and food they need to improve their standard of living. Farmers in the higher income bracket are more likely to adopt on-farm tree planting activities due to their greater financial resources and willingness to take on greater levels of risk (Lönnstedt 2012; Ficko and Boncina 2013; Gebru et al. 2019; Kinyili et al. 2020). When farmers adopt a new on farm activity, their circumstances also make it possible to take risks, which they do. The formal education level of household heads and the availability and adequacy of tree saplings are only weakly related to farmers' on-farm tree planting adoption decisions at a 10% significance level. This district's low and similar formal education level makes the feeble relationship between the education level and on-farm tree planting adoption, possibly due to the parallel education status across the entire region.

According to the assessment of the current study, farmers with higher education levels may perceive the risk of compromising food security or monthly income as too great if they adopt on-farm tree planting technology. The assessment of this study confirmed by the studies of Cosmas et al. (2012), Dhiman (2012), Kinyili et al. (2020), and Brockhaus et al. (2021). One barrier to the widespread use of new on-farm technology is the high price of planting stock, directly correlated with the ease with which one may get tree seedlings. The result reported by Ghadim and Pannell (1999), Ashraf et al. (2018), and Kinyili et al. (2020), who evaluated that the accessibility of tree seedlings is associated with it cost of the labor force of farmers' household and land ownership. The farmers on farm tree planting decision is determined by several factors, including land and labor, or a combination of the two, as well as education level, ease of access to planting stocks, and the cost of planting stocks. The main determining factors for planters to adopt trees on their farms, due to their considerable variability, loan information (V10) and awareness of insurance facilities (V11) cannot be used as explanatory factors for adaptation. We speculate that this diversity is due to a critical need for more distribution to promote these services among the farmers in the area due to poor awareness of farmers and governmental organizations.

The results of the current study's model analysis, combined with the theory and constants from previous research, indicate that the variable V1 in the evaluated statistic model strongly correlates adversely with the practice of on-farm tree planting activities. There is a negative correlation between the age of household head and the number of trees planted on agricultural land by the farmers. This may be because of young farmers are more willing to take risks and have a long-term planning horizon than those with a high age level. This evaluation is in agreement with the findings from various studies conducted by Suyanto et al. (2005), Sharma et al. (2009), Tremblay et al. (2014) Saha et al. (2018), and Kinyili et al. (2020). Their results indicate that younger farmers' heads are more eager to embrace new technology, and they are more equipped to harvest crops, fruit, and vegetables than their more senior counterparts. This is because younger family heads are more ready to take risks than elder people are, and fewer trees are planted as the average age of a household's head rises. A farmer's household is less likely to embrace cutting-edge farming methods if its members have large families. It was hypothesized that bigger families would utilize more of their property to provide for their members' needs. In contrast, smaller families could do so with a minor portion of their farmlands and may devote the remaining farmland areas to the agroforestry system. Kinyili et al. (2020) research notes that many relatives have no noticeable impact. There was no positive significant statistical relationship between the availability of agricultural insurance and loans and measures of wealth or risk tolerance. This might be because of the low diversity of loan facilities among the families of the farmers in this area and the poor performance of the loan agencies responsible for delivering these services. Loan, and credit facility, and availability were shown to be a significant problem in future tree planting following the advice that confidence intervals were computed for the variables of investigated parameters in the logistic regression statistical regression model, as confirmed by Agresti (1996); Ashraf et al. (2018), Kinyili et al. (2020). This allowed us to assess model parameters' influence, extent, and significance. There are 95% confidence intervals for all of the examined critical parameters in the model utilized in this investigation. The data highlight the verified impacts on the adoption of these factors, and the tight confidence ranges double confirm this.

In conclusion, an increasing demand for forest non-timber products and the harvesting of trees for fuel wood and timber for housing and development activities (Adesina et al. 2000; Brockhaus et al. 2021), including large and small-scale agriculture are the main causes of natural forest cover losses that led to extensive deforestation in developing nations (Kulindwa 2016; Brockhaus et al. 2021). This study was set to examine the factors influencing the tree-planting horizons of farmers to adopt agroforestry technology. A binary logistic regression statistic model was proposed to assess the influencing factors on the decision of 160 regional farmers from 32 villages of the northern-east of Afghanistan agro-ecological region. The finding of this study highlighted that several variables affect both the choice to plant trees and the intensity of agroforestry technology. The empirical results deemed the high income of the farmer's household head, the availability of irrigated land, the amount of cropping land, and the farmers' previous experience with tree planting on their own farms are the most influencing factors to adopt plantings of trees on their farmland.

On the other hand, factors such as education, limited access to planting materials, large family size, availability of tree seedlings, age of family head, and insurance and loan facilities influenced farmers' decisions and adaptation practices towards tree planting. However, short-term training is critical driver in helping farmers understand modern innovation's possibilities, challenges, and requirements. Further, these influencing factors may need to evolve over time following the course of agroforestry adaptation practices and society to help reduce the age bias towards agroforestry adoption that has been seen to date. Sustainable techniques such as agroforestry must spread widely, and social media may play an important role. The urgency and importance of increasing data sets to approve other impactful strategies, such as improving the service offerings of loan and insurance organizations, cannot be overstated. Policy support is critical to successfully implementing this technology as it develops and becomes popular. Furthermore, as biophysical circumstances vary among the regions in Afghanistan. This study also calls for more investigation into the design of tree-planting incentives for farmers in various agro-ecological zones properly, on rain-fed hill terrain agriculture. Meanwhile, this portion of the agricultural land area is insufficiently explored.

The findings of this study might benefit policymakers in Afghanistan and other developing nation facing equivalent challenges, to strengthen the National Agroforestry Policy for creating a massive people's movement to achieve national tree cover targets and minimize the present pressure on existing natural forests and may provide insights into the policies that can be implemented to reduce deforestation and increase farm forest products. The government should develop policies and create programs and networks for farmers, researchers, extension agents, and stakeholders to share information and knowledge on agroforestry and crop management and incentivize farmers to adopt agroforestry practices through financial and technical support for tree planting, establishment of agroforestry demonstration plots, and training programs for farmers. Allocation of more fund towards research and development in agroforestry, and crop management for sustainable land use, food security, and safety, and climate change adoption measure, to ensure the long term and sustainable uses of land and other natural resources to protect biodiversity, ecosystem functions, and services. Such policies and partnerships can help bridge the gap between research and practice and facilitate the development and adoption of innovative technologies and practices. This study has highlighted the need and opportunity for further research in on-farm tree plantation and socio-demographic dimensions, and may provide a basis to modify the existing framework and policies in the various developing and under developed countries.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the support of the Agriculture Faculty of Kunduz University, Afghanistan, for providing field visit facilities. Special thanks go to the farmers of Imam Sahib District of Kunduz Province, Afghanistan, for their invaluable contributions to this study, including participation in the field survey, face-to-face interviews, focus group discussions, and provision of expertise.

REFERENCES

Adesina AA, Mbila D, Nkamleu GB, Endamana D. 2000. Econometric analysis of the determinants of adoption of alley farming by the farmers in the forest zone of southern Cameroon. Agric Econ Syst Environ 80 (3): 255-265. DOI: 10.1016/S0167-8809(00)00152-3.

Agresti A. 1996. An Introduction to Categorical Data Analysis. John Wiley and Sons, New York.

Aich V, Khoshbeen AJ. 2016. Afghanistan: Climate Change Science Perspectives. National Environmental Protection Agency (NEPA) and UN Environment, Kabul.

Akinnifesi FK, Chirwa PW, Ajayi OC, Sileshi G, Matakala P, Kwesiga FR, Harawa H, Makumba W. 2008. Contributions of agroforestry research to livelihood of smallholder farmers in southern Africa: Taking stock of the adaptation, adoption and impact of fertilizer tree options. Agric J 3 (1): 58-75.

Ali A, Erenstein O. 2017. Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. Clim Risk Manag 1 (2): 35-48. DOI: 10.1016/j.crm.2016.12.001.

Ashraf J, Rajiv P, Jong WD, Nagar B. 2018. Factors influencing farmers'' decisions to plant trees on their farms in Uttar Pradesh, India. J For Environ Sci 2 (3): 256-267. DOI: 10.1007/s11842-015-9289-7.

Basamba TA, Mayanja C, Kiiza B, Nakileza B, Matsiko F, Nyende P, Kukunda EB, Tumushabe A, Ssekabira K. 2016. Enhancing adoption of agroforestry in the eastern agro-ecological zone of Uganda. Intl J Ecol Sci Environ Eng 3 (1): 20-31.

Belda M, Haltanová E, Holenke T, Kavlová J. 2014. Climate classification revisited: From Koëppen to Trewartha. Clim Res 59: 1-13. DOI: 10.3354/cr01204.

Brockhaus M, Gregoria , Djoudi H, Moleiono M, Pham TT, Wong GY. 2021. The forest fontier in the global south: Climate change policies and the promise of development and equity. Ambio 1 (2): 346-351. DOI: 10.1007/s13280-021-01602-1.

Buyinza M, Wambede N. 2008. Extension for agroforestry technology adoption: Mixed intercropping of crotalaria (*Crotalaria grahamiana*) and maize (*Zea mays* L.) in Kabale District, Uganda. Environ Res J 2 (3): 131-137.

Cosmas P, Christopher G, Chaarles K, Vincent TM. 2012. A review of agro forestry technologies adoption among smallholder farmers in Zimbabwe. J Sustain Dev Stud 1 (1): 68-92.

CSO. 2017. Socio-Demographic and Economic Survey. Survey Report of Central Statistic Organization, Kabul, Afghanistan.

Dhiman CR. 2012. Transforming rural Uttar Pradesh through integrating tree culture on farm land: A case study of WIMCO''s Poplar Programme. Lucknow Manag Assoc Conv J 8 (1): 85-98.

Faham E, Rezvanfar A, Shamekhi T. 2008 Analysis of factors influencing motivation of villagers' participation in activities of social forestry (the case study of West Mazandaran). Am J Agric Biol Sci 3 (2): 451-456. DOI: 10.3844/ajabssp.2008.451.456.

FAO. 2003. Trees and Bushes of Afghanistan. Rome Italy.

FAO. 2012. Country Profile – Afghanistan. FAO Aquastat Report, Version 2012. Rome, Italy.

FAO. 2016. Land Cover Atlas of the Islamic Republic of Afghanistan. FAO, Kabul, Afghanistan.

FAO. 2018. 15 Years in Afghanistan a Special Report: 2003-2018. Rome.

Ficko A, Boncina A. 2013. Probabilistic typology of management decision making in private forest properties. For Policy Econ 27: 34-43. DOI: 10.1016/j.forpol.2012.11.001.

Gebru BM, Wang SW, Kim SJ, Lee WK. 2019. Socio-ecological niche and factors affecting agroforestry practice adoption in different agro-ecologies of southern Tigray, Ethiopia. Sustainability 11 (13): 729. DOI: 10.3390/su11133729.

Ghadim AKA, Pannell DJ. 1999. A conceptual framework of adoption of an agricultural innovation. J Intl Assoc Agric Econ 21 (2): 145-154. DOI: 10.1111/j.1574-0862.1999.tb00590.x.

Groninger, John W. 2014. Forestry and Forestry education in Afghanistan. J For 104 (8): 426-430. DOI: 10.1093/jof/104.8.426.

Jara-Rojas R, Russy S, Roco L, Fleming-Muñoz D, Engler A. 2020. Factors affecting the adoption of agroforestry practices: Insights from silvopastoral systems of Colombia. Forests 11: 684. DOI: 10.3390/f11060648.

Khurram S, Shalizi MN, Bashari M, Akamani K, Groninger JW. 2024. Barriers and opportunities regarding community-based forest management in Afghanistan: considerations for fragile states. Environ Conserv 51 (1): 6-16. DOI: 10.1017/S0376892923000280.

Kinyili BM, Ndunda E, Kitur E. 2020. Socio-economic and institutional factors influencing adoption of agroforestry in arid and semi-arid (ASALs) areas of Sub Saharan Africa. Intl J For Hortic 6 (1): 8-18. DOI: 10.20431/2454-9487.0601002.

Kulindwa YJ. 2016. Key factors that influence households' tree planting behavior. Nat Resour Forum 40 (1-2): 37-50. DOI: 10.1111/1477-8947.12088.

Lambert O, Ozioma AF. 2011. Adoption of improved agroforestry technologies among contact farmers in Imo State, Nigeria. Asian J Agric Rural Dev 2 (1): 1-9.

Lönnstedt L. 2012. Small Scale forest owners' responsibilities: Results from a Swedish Case Study. Small-scale For 11 (3): 407-416. DOI: 10.1007/s11842-011-9187-6.

Magugu JW, Feng S, Ototo G. 2018. Socio-economic factors affecting agro-forestry technology adoption in Nyando, Kenya. J Water Land Dev 39 (1): 83-91. DOI: 10.2478/jwld-2018-0062.

Ministry of Agriculture Irrigation and Livestock (MAIL). 2019. Resettlement due Diligence Report AFG: Panj Amu River Basin Sector Projects. Ministry of Agriculture Irrigation and Livestock, Kabul, Afghanistan.

Moheb Z, Jahid N, Noori H. 2016. Bactrian Deer (*Cervus elaphus bactrianus*) still exist in Afghanistan. DSG Newsl 28: 5-12.

NEPA. 2019. Afghanistan' Afghanistan''s sixth National Report to The United Nation''s Convention on Biological Diversity. National Environmental Protection Agency Kabul, Afghanistan.

Neupane RP, Sharma KR, Thapa GB. 2002. Adoption of agroforestry in the hills of Nepal: A logistic regression analysis. Agric Syst 72 (3): 177-196. DOI: 10.1016/S0308-521X (01)00066-X.

Omerkhil N, Chand T, Valente D, Alatalo JM, Pandey R. 2020. Climate change vulnerability and adaptation strategies for smallholder farmers in Yangi Qala District, Takhar, Afghanistan. Ecol Indic 110: 105863. DOI: 10.1016/j.ecolind.2019.105863.

Place F, Ajayi OC, Torquebiau E, Detlefsen G, Gauthier M, Buttoud G. 2012. Improved Policies for Facilitating the Adoption of Agroforestry. In: Kaonga ML (eds). Agroforestry for Biodiversity and Ecosystem Services: Science and Practice. IntTechOpen, Rijeka. DOI: 10.5772/34524.

Raina R, Hara SS, Hara V, Irland LC. 2011. Twenty-first century forest plantations: Development of agroforestry in Haryana. J Resour Energy Dev 8 (2): 67-74. DOI: 10.3233/RED-120084.

Reddy CS, Saranya KRL. 2017. Earth observation data for assessment of nationwide land cover and long-term deforestation in Afghanistan. Glob Planet Chang 155: 155-164. DOI: 10.1016/j.gloplacha.2017.07.005.

Sadiq GA, Omerkhil N, Zada KA, Safdary AJ. 2019. Evaluation of growth and yield performance of five cucumbers (*Cucumis sativus* L.) genotypes; Case study Kunduz Province, Afghanistan. Intl J Adv Educ Res 4 (6): 22-28.

Saha S, Sharmin A, Biswas R, Ashaduzzaman MD. 2018. Farmers' Perception and Adoption of Agroforestry Practices in Faridpur District of Bangladesh. Intl J Environ Agric Biotechnol 3 (6): 1987-1994. DOI: 10.22161/ijeab/3.6.5.

Shalizi MN, Khurram S, Groninger JW, Ruffner CM, Burney OT. 2018. Indigenous knowledge and stand characteristics of a threatened tree species in a highly insecure area: Chilgoza pine in Afghanistan. For Ecol Manag 413: 1-8. DOI: 10.1016/j.foreco.2018.01.053.

Sharma SK, Sudhir C, Sharma SK, Kaur B, Arya ID. 2009. Opportunities and major constraint''s in agroforestry systems of western UP: A vital role of Star Paper Mills, Saharanpur (UP) – India. Agric Biol J N Am 1 (3): 343-349. DOI: 10.5251/abjna.2010.1.3.343.349.

Shin S, Soe KT, Lee H, Kim TH, Lee S, Park MS. 2020. A systematic map of agroforestry research focusing on ecosystem services in the Asia-Pacific Region. Forests 11: 368. DOI: 10.3390/f11040368.

Sidibe M. 2005. Farm-level adoption of soil and water conservation techniques in northern Burkina Faso. Agric Water Manag 71 (3): 211-224. DOI: 10.1016/j.agwat.2004.09.002.

Suyanto S, Permana RP, Khususiyah N, Joshi N. 2005. Land tenure, Agroforestry Adoption, and reduction of fire hazard in a forest zone: A case study from Lampung, Sumatra, Indonesia. Agrofor Syst 65: 1-11. DOI: 10.1007/s10457-004-1413-1.

Tefera SA, Lerra MD. 2016. Determinants of farmers decision making for plant *Eucalyptus* trees in Market District, North Willow, Ethiopia. Res Hum Soc Sci 6 (13): 123-146.

Thangata PH, Alavalapati JRR. 2003. Agroforestry adoption in southern Malawi: The case of mixed intercropping of *Gliricida sepium* and maize. Agric Syst 78 (1): 57-71. DOI: 10.1016/S0308-521X(03)00032-5.

Tremblay S, Lucotte M, Revert JP, Davidson R, Mertens F, Passos JS, Romana CA. 2014. Agroforestry systems as a profitable alternative to slash and burn practices in small-scale agriculture of the Brazilian Amazon. Agrofor Syst 89: 193-204. DOI: 10.1007/s10457-014-9753-y.

UNEP. 2013. Afghanistan Post-Conflict Environmental Assessment; First Published in Switzerland by the United Nations Environment Programme. First published in Switzerland by the University of Notre Dame Afghanistan Notre Dame Global Adaptation Index. http://index.gain.org/country/afghanistan

USAID. 2017. Kunduz Province profile. College of Agriculture and Environmental Sciences. International Programs ip. ucdavis. edu. USAID report, 2017, http:// Afghanag.ucdavis. edu/ Afghanistan-province-agriculture profile.

WMO. 2018. The State of the Global Climate in 2018 (World Meteorological Organization), DOI: 10.1029/2018GL079362.

Zomer RJ, Bossio DA, Trabucco A, Yuanjie L, Gupta DC, Singh VP. 2007. Trees and Water: Smallholder Agroforestry on Irrigated lands in Northern India. IWMI Research Report 122 International Water Management Institute, Colombo Sri Lanka.